Package ‘SurviMChd’

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Title High Dimensional Survival Data Analysis with Markov Chain Monte Carlo

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Depends R (>= 3.5.0)

Imports rjags,R2jags,dplyr

LazyData Yes

LazyDataCompression xz

ByteCompile Yes

Description High dimensional survival data analysis with Markov Chain Monte Carlo(MCMC). Currently supports frailty data analysis. Allows for Weibull and Exponential distribution. Includes function for interval censored data.

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Encoding UTF-8

NeedsCompilation no

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RoxygenNote 7.3.1

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Repository CRAN

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R topics documented:

`fraidm` *Frailty with Discrete Mixture Model*

Description

Discrete mixture model with MCMC

Usage

```
fraidm(m, n, Ins, Del, Time, T.min, chn, iter, data)
```

Arguments

`m`	Starting column number form where study variables to be selected.
`n`	Ending column number till where study variables will get selected.
`Ins`	Variable name of Institute information.
`Del`	Variable name containing the event information.
`Time`	Variable name containing the time information.
`T.min`	Variable name containing the time of event information.
`chn`	Number of MCMC chains
`iter`	Define number of iterations as number.
`data`	High dimensional data, event information given as (delta=0 if alive, delta=1 if died). If patient is censored then t.min=duration of survival. If patient is died then t.min=0. If patient is died then t=duration of survival. If patient is alive then t=NA.

Details

By given m and n, a total of 3 variables can be selected.

Value

fraidmout - b[1] is the posterior estimate of the regression coefficient for first covariate.

b[2] is the posterior estimate of the regression coefficient for second covariate.

b[3] is the posterior estimate of the regression coefficient for third covariate.

omega[1] and omega[2] are frailty effects.

c[1] and c[2] are regression intercept and coefficients of covariates over mean effect.

References

Bhattacharjee, A. (2020). Bayesian Approaches in Oncology Using R and OpenBUGS. CRC Press.

Congdon, P. (2014). Applied bayesian modelling (Vol. 595). John Wiley & Sons.

See Also

fraidpm frairand

Examples

```
##
data(frailty)
fraidm(m=5,n=7,Ins="institute",Del="del",Time="timevar",T.min="time.min",chn=2,iter=6,data=frailty)
##
```

`fraidpm` *Frailty with drichlet process mixture*

Description

Frailty analysis on high dimensional data by Drichlet process mixture.

Usage

```
fraidpm(m, n, Ins, Del, Time, T.min, chn, iter, adapt, data)
```

Arguments

`m`	Starting column number form where study variables to be selected.
`n`	Ending column number till where study variables will get selected.
`Ins`	Variable name of Institute information.
`Del`	Variable name containing the event information.
`Time`	Variable name containing the time information.
`T.min`	Variable name containing the time of event information.
`chn`	Number of MCMC chains.
`iter`	Define number of iterations as number.
`adapt`	Define number of adaptations as number.
`data`	High dimensional data, event information given as (delta=0 if alive, delta=1 if died). If patient is censored then t.min=duration of survival. If patient is died then t.min=0. If patient is died then t=duration of survival. If patient is alive then t=NA.

Details

By given m and n, a total of 3 variables can be selected.

Value

fraidpmout omeg[i] are frailty effects.

Author(s)

Atanu Bhattacharjee and Akash Pawar

References

Bhattacharjee, A. (2020). Bayesian Approaches in Oncology Using R and OpenBUGS. CRC Press.

Congdon, P. (2014). Applied bayesian modelling (Vol. 595). John Wiley & Sons.

See Also

fraidm frairand

Examples

```
##
data(frailty)
fraidpm(m=5,n=7,Ins="institute",Del="del",Time="timevar",T.min="time.min",chn=2,iter=6,
adapt=100,data=frailty)
##
```

`frailty` *Frailty in high dimensional survival data.*

Description

Data set listing institutional wise survival outcomes

Survival observations data for frailty model functions of SurviMChd

Usage

```
data(frailty)
```

Format

A `tibble` with 7 columns and 272 rows which are :

institute Institute of the sample observations

del Numberic values 0 or 1 containing death/event information

timevar Survival duration

time.min Minimum survival

female Covariate_1, gender variable indicating either a female or not

ph.karno Covariate_2

pat.karno Covariate_3

Examples

```
data(frailty)
```

`frairand` *Frailty with random effects in high dimensional data with MCMC*

Description

Random effects frailty model

Usage

```
frairand(m, n, Ins, Del, Time, T.min, chn, iter, adapt, data)
```

Arguments

`m`	Starting column number form where study variables to be selected.
`n`	Ending column number till where study variables will get selected.
`Ins`	Variable name of Institute information.
`Del`	Variable name containing the event information.
`Time`	Variable name containing the time information.
`T.min`	Variable name containing the time of event information.
`chn`	Numner of MCMC chains.
`iter`	Define number of iterations as number.
`adapt`	Define number of adaptations as number.
`data`	High dimensional data having survival duration, event information and column of time for death cases.

Details

By given m and n, a total of 3 variables can be selected.

Value

frairandout omeg[i] are frailty effects.

Author(s)

Atanu Bhattacharjee and Akash Pawar

References

Tawiah, R., Yau, K. K., McLachlan, G. J., Chambers, S. K., & Ng, S. K. (2019). Multilevel model with random effects for clustered survival data with multiple failure outcomes. *Statistics in medicine*, **38(6)**, 1036-1055.

See Also

fraidm fraidpm

Examples

```
##
data(frailty)
frairand(m=5,n=7,Ins="institute",Del="del",Time="timevar",T.min="time.min",chn=2,iter=6,
 adapt=100,data=frailty)
##
```

---

headnneck *High dimensional genomic data on head and neck cancer*

Description

Head and neck cancer data `tibble` on head and neck cancer patients for survexpMC and survweibMC functions.

Usage

```
data(headnneck)
```

Format

A `tibble` with 13 columns which are :

Subjects Patients referred to as Subjects

OS Overall Survival

Death Death status for the particular subjects

randgrp1 Arm of group assigned to subjects

gender1 Demographic information of Subjects, i.e. Gender

Stratum1 Stratum from where the sample is drawn

prevoi Categorical observation

Covariate_1 Continuous observations

Covariate_2 Continuous observations

Covariate_3 Continuous observations

Covariate_4 Continuous observations

Covariate_5 Continuous observations

Covariate_6 Continuous observations

Examples

```
data(headnneck)
```

---

hnscc *hnscc Head and neck cancer data*

Description

High dimensional head and neck cancer gene expression data

Usage

```
data(hnscc)
```

Format

A dataframe with 565 rows and 104 variables

ID ID of subjects

leftcensoring Initial censoring time

death Survival event

os Duration of overall survival

PFS Duration of progression free survival

Prog Progression event

GJB1,...,HMGCS2 High dimensional covariates

Examples

```
data(hnscc)
```

`mcsurv` *Metronomic cancer data*

Description

Observations made `tibble` on the head and neck cancer patients. Data for survMC function from SurviMChd package.

Usage

```
data(mcsurv)
```

Format

A `tibble` with 15 columns which are :

OS Overall Survival

Death Death status

t Time at which event occurred

x1 Variable measured on continuous scale

x2 Variable measured on discrete scale

x3 Variable measured on continuous scale

x4 Variable measured on discrete scale

x5 Variable measured on continuous scale

Examples

```
data(mcsurv)
```

`survexpMC` *Exponential survival analysis with MCMC*

Description

Survival analysis with exponential distribution by MCMC

Usage

```
survexpMC(m1, n1, m2, n2, chains, iter, data)
```

Arguments

`m1`	Starting column number from where variables of high dimensional data will be selected.
`n1`	Ending column number till where variables of high dimensional data will get selected.
`m2`	Starting column number from where demographic observations starts
`n2`	Ending column number of the demographic observations
`chains`	Number of MCMC chains
`iter`	Number of MCMC iterations
`data`	High dimensional data having survival duration as (OS), event information as Death (1 if died, or 0 if alive).

Value

survexpMCout A data set listing estimated posterior means and deviances

Author(s)

Atanu Bhattacharjee and Akash Pawar

References

Kumar, M., Sonker, P. K., Saroj, A., Jain, A., Bhattacharjee, A., & Saroj, R. K. (2020). Parametric survival analysis using R: Illustration with lung cancer data. *Cancer Reports*, **3**(**4**), e1210.

See Also

survweibMC

Examples

```
##
data(headnneck)
survexpMC(m1=8,n1=12,m2=4,n2=7,chains=2,iter=10,data=headnneck)
##
```

`survMC` *Survival analysis using Cox Proportional Hazards with MCMC.*

Description

Performs survival analysis using Cox Proportional Hazards with MCMC.

Usage

```
survMC(m, n, Time, Event, chains, adapt, iter, data)
```

Arguments

`m`	Starting column number from where variables of high dimensional data will get selected.
`n`	Ending column number till where variables of high dimensional data will get selected.
`Time`	Variable/Column name containing the information on duration of survival
`Event`	Variable/Column name containing the information of survival event
`chains`	Number of chains to perform
`adapt`	Number of adaptations to perform
`iter`	Number of iterations to perform
`data`	High dimensional data having survival duration and event.

Details

The survival columns of the data should be arranged as follows - Death Death status=1 if died otherwise 0. OS Survival duration measured as 'OS' t.len Number of censored times

Value

Data set containing Posterior HR estimates, SD and quantiles.

Author(s)

Atanu Bhattacharjee and Akash Pawar

References

Bhattacharjee, A. (2020). Bayesian Approaches in Oncology Using R and OpenBUGS. CRC Press.

See Also

survintMC

Examples

```
##
data(mcsurv)
survMC(m=4,n=8,Time="OS",Event="Death",chains=2,adapt=100,iter=1000,data=mcsurv)
##
```

`survMCmulti` *Survival analysis on multiple variables with MCMC*

Description

Performs survival analysis using Cox Proportional Hazards with MCMC with an option to input select multiple variables.

Usage

```
survMCmulti(
  var1 = NULL,
  var2 = NULL,
  var3 = NULL,
  var4 = NULL,
  var5 = NULL,
  Time,
  Event,
  chains,
  adapt,
  iter,
  data
)
```

Arguments

`var1`	Variable name (first one)
`var2`	Variable name (second one)
`var3`	Variable name (third one)
`var4`	Variable name (fourth one)
`var5`	Variable name (fifth one)
`Time`	Variable/Column name containing the information on duration of survival
`Event`	Variable/Column name containing the information of survival event
`chains`	Number of chains to perform
`adapt`	Number of chains to perform
`iter`	Number of iterations to perform
`data`	High dimensional data having survival duration and event.

Details

The survival columns of the data should be arranged as follows - Death Death status=1 if died otherwise 0. OS Survival duration measured as 'OS'

Value

Data set containing Posterior HR estimates, SD, quantiles and meandeviance.

Author(s)

Atanu Bhattacharjee and Akash Pawar

References

Bhattacharjee, A. (2020). Bayesian Approaches in Oncology Using R and OpenBUGS. CRC Press.

See Also

survintMC

Examples

```
##
data(mcsurv)
survMCmulti(var1="x1",var2=NULL,var3="x3",var4="x2",
   var5="x4",Time="OS",Event="Death",chains=2,adapt=100,iter=1000,data=mcsurv)
##
```

`survweibMC` *Weibull survival analysis with MCMC*

Description

Survival analysis with weibull distribution by MCMC

Usage

```
survweibMC(m1, n1, m2, n2, chains, iter, data)
```

Arguments

m1	Starting column number from where variables of high dimensional data will be selected.
n1	Ending column number till where variables of high dimensional data will get selected.
m2	Starting column number from where demographic observations starts
n2	Ending column number of the demographic observations
chains	Number of MCMC chains
iter	Number of MCMC iterations
data	High dimensional data having survival duration as (OS), event information as Death (1 if died, or 0 if alive).

Value

beta1[1] Posterior estimates of regression coefficients and deviance

Author(s)

Atanu Bhattacharjee and Akash Pawar

References

Kumar, M., Sonker, P. K., Saroj, A., Jain, A., Bhattacharjee, A., & Saroj, R. K. (2020). Parametric survival analysis using R: Illustration with lung cancer data. *Cancer Reports*, **3(4)**, e1210.

Khan, S. A. (2018). Exponentiated Weibull regression for time-to-event data. *Lifetime data analysis*, **24(2)**, 328-354.

See Also

survexpMC

Examples

```
##
data(headnneck)
survweibMC(m1=8,n1=12,m2=4,n2=7,chains=2,iter=10,data=headnneck)
##
```

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